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A Spatial Econometric Analysis of Healthcare Spending and Medical Resource Allocation Effects on County-Level In-Migration in Taiwan

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Abstract

This study aims to investigate the effects of healthcare spending and medical resource allocation on county-level in-migration in Taiwan, with a particular focus on the spatial spillover effects. Using balanced panel data from 22 counties and cities across Taiwan between 2000 and 2023, this research adopts the Spatial Durbin Model (SDM) within the framework of spatial econometrics to capture the spatial interdependencies and regional linkages resulting from geographic proximity. The empirical findings reveal that certain indicators of medical resource availability—such as the density of healthcare facilities and nursing personnel—exert significant positive effects not only on local in-migration but also on that of neighboring regions, highlighting the critical role of healthcare accessibility in influencing migration decisions. In contrast, government healthcare expenditure shows a negative relationship with in-migration, which may reflect inefficiencies in resource allocation and local implementation. This study confirms the relevance of Tobler's First Law of Geography in the context of migration and emphasizes the importance of adopting a regionally integrated policy perspective to improve the equity of population mobility and manage policy externalities effectively.

JEL classification numbers: H51, I18, R23.
Keywords: Spatial econometric model, Healthcare spending, Medical resources, In-migration, Spatial spillover effects.

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1. Introduction

With the growing disparities between urban and rural development and the accelerating trend of population aging, the allocation of medical resources and the distribution of healthcare expenditure have become critical factors influencing internal migration. Previous studies have pointed out that the accessibility, quality, and scale of regional healthcare services may significantly affect individuals' willingness to migrate, thereby reshaping the demographic structure of local areas (Finkelstein, Gentzkow, and Williams, 2016). In highly centralized health systems such as Taiwan's National Health Insurance (NHI), geographic differences in healthcare resource allocation and spending strategies may generate notable regional spillover effects, particularly in terms of population movements across counties and cities.

Moscone and Knapp (2005), through spatial econometric analysis of mental healthcare spending in the UK, revealed that even adjacent regions exhibited strong policy interdependence and spending chain reactions. Similarly, Zhang et al. (2019) found spatial dependencies in healthcare spending and out-of-pocket rates across Chinese provinces, with significant effects on neighboring regions' migration flows. In addition, Guo and Luo (2019) highlighted the spatial concentration of medical resources in China, emphasizing how uneven distribution exacerbates regional health inequalities and social disparity.

On the methodological front, spatial econometric models have gained increasing attention in recent years for evaluating policy interventions and resource allocation effects across neighboring regions (Baltagi, Moscone, and Santos, 2018). These models are particularly suitable for analyzing whether migration patterns are affected by healthcare spending and medical resource availability in adjacent areas. Traditional regression models typically assume independence among observations, which neglects the spatial interactions and externalities that exist in real-world geographic settings. Variables such as public health expenditure and medical resource distribution often exhibit spatial dependence, influencing not only the local area but also extending to neighboring regions, thus shaping migration decisions. Ignoring such spatial interdependencies can lead to biased and inconsistent parameter estimates (Baltagi et al., 2018).

Spatial econometric models effectively address this issue by incorporating spatial weight matrices and spatially lagged terms to capture interregional interactions and spillover effects. The spatial autoregressive model (SAR) captures spatial dependence in the dependent variable, while the spatial error model (SEM) accounts for spatially correlated error terms. The spatial Durbin model (SDM), which includes both spatial lags of the dependent and independent variables, offers a more comprehensive and robust approach and is widely applied in regional analysis (Moscone and Knapp, 2005). Therefore, employing spatial econometric models enables a more thorough assessment of how healthcare spending and medical resource allocation influence migration behavior and provides a foundation for more precise policy design.

Despite the relevance of this topic, there remains a paucity of empirical research in the context of Taiwan that examines, at the county level, the impact of healthcare expenditure and medical resource allocation on in-migration using spatial econometric methods. This study seeks to fill this empirical gap by applying the Spatial Durbin Model (SDM) to analyze both the direct and indirect (spillover) effects of healthcare expenditure and resource distribution on inter-county in-migration in Taiwan. The findings aim to offer evidence-based implications for public policy concerning medical resource reallocation and balanced population development.

The main objectives of this study are as follows: (1) to examine the direct effects of healthcare spending and medical resource allocation on in-migration across counties and cities in Taiwan; and (2) to assess the spatial spillover effects of healthcare spending and medical resource allocation on neighboring regions. By integrating theoretical insights and empirical analysis, this research intends to provide practical implications and policy recommendations for regional economic planning.

The following chapters will review relevant literature and develop the research hypotheses, introduce the research design including data, sample, variables, and empirical models, and present descriptive statistics and correlation analysis. Subsequently, the spatial Durbin model estimation results will be discussed, along with an analysis of direct and spatial spillover effects. Finally, research conclusions and policy implications will be provided.

2. Hypothesis Development

2.1 The impact of local healthcare spending on in-migration

Government expenditure on healthcare represents the extent to which local governments invest in public health and the well-being of residents. The scale and structure of such spending often reflect the accessibility and quality of regional medical services (Finkelstein et al., 2016). Under a universal healthcare system such as Taiwan's National Health Insurance (NHI), while central government funding constitutes the majority, fiscal contributions at the local level may still influence the adequacy of medical infrastructure and the availability of healthcare personnel, thereby affecting the county or city's ability to attract in-migrants.

An empirical study by Balia, Brau, and Marrocu (2018) on Italy showed that local government healthcare expenditures and hospital resources significantly affected patient migration behavior across regions. Similarly, Wan et al. (2021) conducted a spatial analysis at the county level in China and found that government healthcare spending and the distribution of medical resources exerted significant spatial effects on population flows, including notable spillover effects to adjacent areas. Furthermore, Wan and Wang (2024) applied spatial econometric methods in the Chinese context and confirmed that public health fiscal expenditure exhibits strong spatial autocorrelation, with impacts not limited to the local jurisdiction but also extending to influence migration behavior in neighboring regions.

In light of this, the present study posits that counties or cities with higher levels of healthcare-related spending—or a greater proportion of healthcare expenditure within the overall government budget—may provide better medical service quality and health security, thereby becoming more attractive to in-migrants.

Hypothesis 1: County-level healthcare spending (including total government healthcare expenditure and the proportion of healthcare expenditure in overall government spending) significantly affects local in-migration.

2.2 Spatial spillover effects of fiscal expenditure in neighboring regions

In addition to a county's own healthcare spending and medical resource allocation influencing in-migration, the policies and resource levels of neighboring regions may also indirectly affect migration patterns through spatial spillover effects. This phenomenon is widely recognized in spatial econometrics as a key feature of regional interaction, particularly in contexts where healthcare spending and medical resource distribution exhibit geographical continuity (Moscone and Knapp, 2005). Finkelstein et al. (2016), in a study on elderly migration in the United States, found that healthcare expenditure and care quality in neighboring areas significantly guided residents' migration decisions. Zhang et al. (2019), using empirical data from county-level analysis in China, further showed that the proportion of out-of-pocket healthcare expenses and the density of medical provision in neighboring counties significantly impacted local healthcare utilization and population mobility. Wan and Wang (2024), applying a Spatial Durbin Model, also confirmed that public health fiscal spending not only affects local population dynamics but also displays strong spatial diffusion effects, generating externalities that influence adjacent regions.

Taken together, these findings suggest that when neighboring counties or cities demonstrate higher levels of healthcare spending, or allocate a greater share of their government budgets to health services, the overall regional healthcare attractiveness increases. This may lead to a clustering effect in population migration, where individuals are drawn toward regions with superior medical environments, thereby increasing the in-migration scale of a given locality.

Hypothesis 2: Healthcare spending in neighboring counties (including total government healthcare expenditure and the proportion of healthcare expenditure in overall government spending) significantly affects a county's in-migration.

2.3 The impact of local medical resource allocation on in-migration

The allocation of medical resources—such as the density of healthcare institutions, the workload of medical personnel, and the geographic coverage of services—directly influences residents' access to healthcare services in terms of both convenience and quality. These factors have become increasingly important considerations in regional population migration decisions. Generally, if a region has

relatively abundant medical resources and each institution or healthcare professional serves fewer people or covers a smaller area, this suggests a lighter service burden and shorter patient wait times, thereby enhancing the region's attractiveness to in-migrants.

Balia et al, (2018) emphasized that the service capacity of medical institutions and the level of personnel allocation significantly affect patients' decisions to seek care across regional boundaries. Pan and Shallcross (2016), in an empirical study at the county level in China, found that resource indicators such as hospital bed density and physician density significantly impacted healthcare accessibility and local population agglomeration. Furthermore, Dong and Wang (2024) examined the spatial distribution of medical resources and concluded that areas with higher resource density are more likely to attract elderly populations and individuals with chronic conditions, contributing to long-term population clustering effects.

Given the notable disparities in the number of healthcare facilities, physician and nursing staff resources, and geographic service coverage across counties and cities in Taiwan, this study incorporates four representative indicators to measure the level of medical resource allocation: (1) average population served per medical institution, (2) average service area per institution, (3) average population served per practicing physician, and (4) average population served per nursing staff member. These variables are employed to explore how local healthcare capacity influences inter-county in-migration.

Hypothesis 3: County-level medical resource allocation—measured by average population served per medical institution, average service area per institution, average population served per practicing physician, and average population served per nursing staff—significantly affects local in-migration.

2.4 Spatial spillover effects of medical resource allocation in neighboring counties

The spatial distribution of medical resources plays a critical role in shaping individuals' geographic choices of residence, and such effects are not confined solely to the local area. Instead, they may extend to neighboring regions through spatial spillover effects (Moscone and Knapp, 2005). According to spatial interdependence theory, individuals tend to consider the availability of public services and quality of life in adjacent regions when deciding where to live. In particular, inter-county commuting and cross-border access to healthcare services make medical resource allocation in neighboring counties a vital determinant of migration behavior (Dong and Wang, 2024).

Pan and Shallcross (2016) highlighted that regional imbalances in hospital bed density and medical personnel in China have driven cross-regional healthcare utilization, affecting the medical burdens and migration dynamics across counties. Similarly, Zhang et al. (2019) found that superior healthcare infrastructure in neighboring areas creates a "pull effect," facilitating regional population

agglomeration as individuals are drawn toward clusters with better medical services. Based on these observations, this study posits that if adjacent counties exhibit lower service burdens per institution and better staffing levels of physicians and nurses, their collective medical service attractiveness may increase. This regional enhancement, in turn, could exert a positive influence on the in-migration of the focal county.

Hypothesis 4: Medical resource allocation in neighboring counties—measured by average population served per medical institution, average service area per institution, average population served per practicing physician, and average population served per nursing staff—significantly affects the in-migration of the focal county.

3. Methodology

3.1 Data and procedure

This study utilizes a panel dataset comprising 22 counties and cities in Taiwan over the period from 2000 to 2023. Taiwan's current administrative structure consists of six special municipalities, thirteen counties, and three provincial cities, which together represent the highest-level units of local self-government. The primary statistical data used in this study were obtained from the Directorate-General of Budget, Accounting and Statistics (DGBAS), specifically from the "Statistical Database of Key County/City Indicators" (2024 release). This dataset provides comprehensive annual information on local government finance, socioeconomic conditions, and industrial structure. Its high degree of completeness and cross-year comparability makes it well-suited for long-term time-series and regional analyses. The empirical framework of this research is grounded in spatial econometrics, with modeling and statistical inference conducted in accordance with standard spatial analytical procedures. To capture potential spatial interactions among Taiwan's counties and cities, a spatial weight matrix was constructed. This matrix is based on a contiguity structure, where counties or cities sharing a common border are considered neighbors, thereby incorporating spatial dependence into the estimation process.

In terms of model specification, this study adopts the Spatial Durbin Model (SDM) as the primary analytical framework. The SDM allows for simultaneous estimation of both within-region (direct) effects and spillover (indirect) effects from neighboring regions, making it particularly suitable for evaluating the dual-level impacts of healthcare spending and resource allocation. To assess the appropriateness of the model, a series of diagnostic tests were conducted, including the Hausman test to determine whether fixed or random effects are more appropriate, and specification tests to examine whether the SDM could be reduced to either a Spatial Autoregressive Model (SAR) or a Spatial Error Model (SEM).

Model selection was further evaluated based on standard goodness-of-fit criteria, including the log-likelihood function, Akaike Information Criterion (AIC), and

Bayesian Information Criterion (BIC). The results of these assessments indicated that the SDM with two-way fixed effects (accounting for both spatial and temporal heterogeneity) offered the best fit, and this model was thus adopted for subsequent analysis.

Finally, an impact decomposition was performed based on the selected spatial model to estimate the direct, indirect (spillover), and total effects of key explanatory variables on county-level in-migration. This decomposition enables a nuanced understanding of how healthcare spending and medical resource allocation affect migration flows both within a region and through its spatial connections. The findings of this study serve as the empirical foundation for comprehensive conclusions and policy recommendations aimed at informing future local public spending and resource allocation strategies.

3.2 Research variables

The definitions and descriptions of the dependent and independent variables used in this study's empirical model are as follows:

Dependent Variable

- In-migration Population (persons) ($\boldsymbol{IM_{it}}$): This variable represents the number of individuals who officially registered as in-migrants in county or city i of Taiwan during year t. It excludes population movements resulting solely from changes in registered residential addresses within the same administrative region.

  Independent Variables Related to Healthcare Expenditure
- Government Healthcare Expenditure (NT$1,000) ($\boldsymbol{GHE_{it}}$): This variable refers to the total finalized expenditure on health and medical services by the local government of county or city i in year t. It includes budget items such as health administration, disease prevention, healthcare services, medical affairs, pharmaceutical regulation, food safety, environmental sanitation, health inspection, health-related infrastructure, and other general health-related categories. It excludes subsidies from the central or higher-level governments.
- Proportion of Healthcare Expenditure to Total Government Expenditure (%) ($\boldsymbol{PHE_{it}}$): This variable measures the share of healthcare spending in relation to the total annual government expenditure for county or city i in year t. It is calculated as:

  (Government Healthcare Expenditure ÷ Total Government Expenditure) × 100

  Independent Variables Related to Medical Resource Allocation
- Average Population Served per Medical Institution (persons/institution) ($\boldsymbol{PSMI_{it}}$): This variable reflects the average number of residents served by each medical institution in county or city i during year t. It is calculated as:

  Registered Population ÷ Number of Medical Institutions
- Average Service Area per Medical Institution (km²/institution) ($\boldsymbol{SAMI_{it}}$): This variable measures the average land area served by each medical institution in county or city i in year t. It is calculated as:

Total Land Area ÷ Number of Medical Institutions

- Average Population Served per Practicing Physician (persons/physician) ($\boldsymbol{PSPP_{it}}$): This variable denotes the average number of residents served by each practicing physician in county or city i during year t. It is calculated as: Registered Population ÷ Number of Practicing Physicians
- Average Population Served per Nursing Staff (persons/nurse) ($\boldsymbol{PSNS_{it}}$): This variable indicates the average number of residents served by each nursing personnel in county or city i during year t. It is calculated as: Registered Population ÷ Number of Nurses

3.3 Empirical model

This study is grounded in Tobler's First Law of Geography, which states: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This theoretical perspective underscores the significance of spatial proximity, positing that geographically adjacent regions are more likely to exhibit intensive socioeconomic interactions and interdependencies - a phenomenon broadly referred to as spatial dependence.

To accurately capture such spatial effects and the potential spillover influences from neighboring regions, this study adopts the Spatial Durbin Model (SDM) proposed by LeSage and Pace (2009) as the core empirical framework. The SDM not only incorporates the spatial lag of the dependent variable, but also includes the spatial lags of the independent variables, thereby enabling a more comprehensive estimation of both direct effects within each locality and indirect (spillover) effects across neighboring jurisdictions. This model is particularly suitable for evaluating the interactive dynamics of regional policy variables and socioeconomic outcomes. Given the objective of examining how healthcare spending and medical resource allocation influence county-level in-migration, while also accounting for the externalities arising from adjacent counties, this study constructs the following Spatial Durbin Model (SDM):

$$\begin{aligned} \boldsymbol{IM_{it}} = \boldsymbol{\rho}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}IM_{jt}} + \boldsymbol{\alpha} + \boldsymbol{\beta_1 GHE_{it}} + \boldsymbol{\beta_2 PHE_{it}} + \boldsymbol{\beta_3 PSMI_{it}} + \boldsymbol{\beta_4 SAMI_{it}} \\ + \boldsymbol{\beta_5 PSPP_{it}} + \boldsymbol{\beta_6 PSNS_{it}} + \boldsymbol{\theta_1}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}GHE_{jt}} + \boldsymbol{\theta_2}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}PHE_{jt}} \\ + \boldsymbol{\theta_3}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}PSMI_{jt}} + \boldsymbol{\theta_4}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}SAMI_{jt}} + \boldsymbol{\theta_5}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}PSPP_{jt}} \\ + \boldsymbol{\theta_6}\sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ij}PSNS_{jt}} + \boldsymbol{\mu_i} + \boldsymbol{\varepsilon_{it}} \\ \mathbf{i \neq j} \end{aligned}$$

In this study, $\boldsymbol{IM_{it}}$ represents the dependent variable, denoting the number of registered in-migrants in county i during year t. Here, i and j refer to different

county-level administrative units in Taiwan, while t indexes the time period spanning from 2000 to 2023.

The term $\boldsymbol{W_{ij}IM_{jt}}$ denotes the spatial weight matrix, which is a square, symmetric matrix of dimension $N \times N$, where $N = 22$ corresponds to the number of counties and cities in Taiwan. In this study, the spatial structure is defined based on the Queen contiguity criterion, which identifies two spatial units as neighbors if they share either a common border or a vertex. Accordingly, $\boldsymbol{W_{ij}} = 1$ if counties i and j are spatially adjacent under this rule, and $\boldsymbol{W_{ij}} = 0$ otherwise. Self-neighboring is not permitted, and thus all diagonal elements $\boldsymbol{W_{ii}}$ are set to 0.

Furthermore, given the geographic isolation of Taiwan's three offshore counties—Penghu County, Kinmen County, and Lienchiang County—which do not share land boundaries with any other counties, their corresponding weights in the contiguity matrix are also set to 0. The formal definition of the spatial weight matrix is as follows:

$$\boldsymbol{W_{ij}} = \begin{cases} \mathbf{1}, & \boldsymbol{regions\ i\ and\ j\ are\ neighboring\ regions} \\ \mathbf{0}, & \boldsymbol{regions\ i\ and\ j\ are\ not\ neighboring\ regions} \end{cases}$$

The term $\boldsymbol{W_{ij}IM_{jt}}$ represents the spatially lagged dependent variable, also known as the spatial autoregressive component of the model. It is an endogenous variable constructed by applying the spatial weight matrix $\boldsymbol{W_{ij}}$ to the dependent variable $\boldsymbol{IM_{it}}$, which denotes the in-migration population of neighboring region j in year t. This term captures the spatial influence that the in-migration activities in neighboring areas exert on the in-migration of region i during the same period, based on geographic proximity.

The parameter ρ is the spatial autoregressive coefficient, which quantifies the direction and magnitude of the spatial dependence among the dependent variable observations across regions. A statistically significant ρ indicates the presence of spatial dependence in the model. If $\rho \neq 0$, this implies that in-migration in one region is spatially correlated with that of its neighbors. Specifically, a positive $\rho > 0$ suggests a positive spatial spillover effect, meaning that higher in-migration in neighboring areas tends to stimulate higher in-migration locally. The magnitude of ρ reflects the extent of spatial diffusion or interregional interaction.

The term α denotes the intercept of the model.

The coefficients $\boldsymbol{\beta_k}$ represent the direct effects of local explanatory variables on the dependent variable. The explanatory variables include: $\boldsymbol{GHE_{it}}$: Government healthcare expenditure (NT$1,000), $\boldsymbol{PHE_{it}}$: Proportion of healthcare expenditure to total government expenditure (%), $\boldsymbol{PSMI_{it}}$: Average population served per medical institution (persons/institution), $\boldsymbol{SAMI_{it}}$: Average service area per medical institution (km²/institution), $\boldsymbol{PSPP_{it}}$: Average population served per practicing physician (persons/physician), $\boldsymbol{PSNS_{it}}$: Average population served per nursing staff (persons/nurse).

The parameters $\boldsymbol{\theta_k}$ capture the spatially lagged effects of the explanatory variables, measuring the indirect (spillover) effects of neighboring regions' fiscal variables and healthcare resource indicators on local in-migration. A positive θ indicates a complementary or spillover effect, whereby better healthcare or fiscal conditions in adjacent regions positively influence local in-migration. Conversely, a negative θ implies a competitive effect among regions.

The term $\boldsymbol{\mu_i}$ denotes the spatial (individual) fixed effect, capturing time-invariant unobservable heterogeneity specific to each county i, such as structural differences across regions. Finally, $\boldsymbol{\varepsilon_{it}}$ represents the random error term, assumed to be independently and identically distributed (i.i.d.), although it may contain unobserved spatial correlation, reflecting latent disturbances in the spatial system not accounted for by the model's explanatory variables.

4. Results

4.1 Descriptive statistics

To better understand the fundamental characteristics of the research sample, this study first conducts descriptive statistical analysis of all variables, with the results presented in Table 1. Based on balanced panel data of 22 counties and cities in Taiwan from 2000 to 2023, the total sample consists of 528 observations.

The average number of in-migrants (IM) is 52,534 persons per county per year, indicating that each locality receives approximately 50,000 new residents annually on average. However, the standard deviation is as high as 49,984, reflecting substantial variation across counties. The maximum value reaches 263,215 persons, highlighting the strong population attraction observed in certain metropolitan areas.

The average government healthcare expenditure (GHE) is NT$865,479 thousand (approximately NT$8.65 billion), with the maximum reaching NT$9,381,196 thousand, suggesting wide disparities in health-related spending among local governments.

As for the proportion of healthcare expenditure to total government expenditure (PHE), the average is 2.14%, while the maximum reaches 11.86%, indicating that some local governments allocate a relatively higher share of their budget to public health services.

Regarding the configuration of healthcare resources, the average number of people served per healthcare facility (PHF) is 1,340, while the average service area per facility (SAHF) is 4.36 square kilometers—both of which reflect uneven access to healthcare between urban and rural areas. The average population served per physician (PPP) is 629 persons, and per nursing staff member (PNP) is 218 persons, suggesting a relatively more sufficient nursing workforce. Nonetheless, some counties still face disproportionately high personnel burdens.

Overall, the descriptive statistics reveal significant inter-county variation in both in-migration and healthcare-related indicators, underscoring the necessity of adopting spatial econometric models to analyze regional interactions and spillover effects more precisely.

To preliminarily explore correlations between key variables, Pearson correlation analysis was conducted, and the results are summarized in Table 2. First, a strong positive correlation is observed between in-migration (IM) and government healthcare expenditure (GHE) ($r = 0.642$, $p < 0.01$), supporting Hypothesis 1: higher local healthcare spending is associated with greater population attraction.

Conversely, the proportion of healthcare expenditure (PHE) exhibits a significant negative correlation with in-migration ($r = -0.213$, $p < 0.01$), suggesting that a high spending ratio does not necessarily indicate high absolute spending. Instead, it may reflect smaller fiscal baselines in certain counties.

Healthcare resource allocation variables—including PHF, SAHF, and PPP—are all significantly negatively correlated with in-migration ($r = -0.358$, -0.399, and -0.250, respectively), indicating that when each medical facility or physician serves a larger population or geographic area, healthcare accessibility and service quality may decline, reducing the region's attractiveness to migrants.

Interestingly, the average population served per nurse (PNP) shows no significant correlation with in-migration ($r = -0.071$). However, PNP and PPP are strongly positively correlated ($r = 0.864$, $p < 0.01$), implying synchronized variations in physician and nursing staff densities in certain counties. This pattern suggests potential multicollinearity, which must be addressed in subsequent regression models.

Table 1: Summary of descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	25th Percentile	Median	75th Percentile	Max.
IM	528	52534.50	60284.64	684.00	15271	23163.5	80927.5	266683.00
GHE	528	865479.15	1220495.89	82687.00	298589.50	425406.5	801367.5	9392272.00
PHE	528	2.14	1.22	.54	1.48	1.815	2.42	11.86
PSMI	528	1340.07	447.84	646.00	1081.68	1294.53	1445.17	3364.50
SAMI	528	4.36	5.52	.07	.74	2.155	5.76	24.24
PSPP	528	629.18	298.28	154.48	423.90	565.65	770.12	1961.31
PSNS	528	218.74	106.31	69.18	144.30	191.89	264.95	648.83

Note: Obs.: Observations.
TWD: New Taiwan dollar (equal to USD 0.030).
IM: In-migration Population (persons), GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km^2/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

Table 2: Pearson correlation analysis

	IM	GHE	PHE	PSMI	SAMI	PSPP	PSNS
IM	1						
GHE	.642**	1					
PHE	-.213**	.151**	1				
PSMI	-.358**	-.356**	.235**	1			
SAMI	-.399**	-.260**	.198**	.264**	1		
PSPP	-.250**	-.369**	.152**	.733**	.164**	1	
PSNS	-.071	-.278**	.290**	.668**	-.023	.864**	1

Note: ** $p<0.01$.
TWD: New Taiwan dollar (equal to USD 0.030).
IM: In-migration Population (persons), GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km²/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

4.2 Results of the Wald test and Likelihood-ratio test

Following the theoretical framework of spatial econometric models proposed by LeSage and Pace (2009) and Elhorst (2010), this study further evaluates whether the Spatial Durbin Model (SDM) can be simplified to either the Spatial Lag Model (SLM) or the Spatial Error Model (SEM). The SDM incorporates both spatially lagged dependent and independent variables, offering greater model flexibility and explanatory power. However, to confirm its appropriateness as the optimal specification, it is essential to test the significance of the spatial lag coefficients of the independent variables, denoted by θ. If the null hypothesis H_0: $\theta = 0$ is rejected, it implies that the SDM cannot be reduced to either SLM or SEM, and the original spatial specification should be retained.

To assess this, the study employs both the Wald test and the Likelihood-Ratio (LR) test to compare the goodness-of-fit of SDM, SLM, and SEM under various model specifications. When comparing SDM with SLM under the spatial fixed-effects framework, the Wald and LR test statistics are $\chi^2 = 12.17$ and $\chi^2 = 12.00$ respectively, both significant at the $p < 0.05$ level, indicating that the SDM outperforms the SLM when accounting for spatial heterogeneity.

Under the time fixed-effects model, the test statistics increase substantially to χ^2 = 126.92 (Wald) and χ^2 = 108.75 (LR), both highly significant ($p < 0.001$), further supporting the SDM's superior capacity to capture temporal heterogeneity. When considering both spatial and time fixed effects simultaneously, the results continue to favor the SDM, with test statistics of χ^2 = 17.21 (Wald) and χ^2 = 11.04 (LR), significant at $p < 0.05$. Even under the random-effects specification, SDM remains preferable to SLM, with χ^2 = 14.28 and χ^2 = 14.02 ($p < 0.05$) for the Wald and LR tests respectively.

In comparisons between SDM and SEM, a similar pattern emerges. Under the spatial fixed-effects specification, the Wald test yields χ^2 = 22.02 and the LR test yields χ^2 = 23.37, reaching significance levels of $p < 0.01$ and $p < 0.001$, respectively. These results indicate that in the presence of substantial spatial structure, the SDM better captures the underlying spatial interactions in the data. The time fixed-effects model produces even stronger evidence in favor of SDM, with Wald and LR test statistics of χ^2 = 107.91 and χ^2 = 103.03 (both $p < 0.001$). In the model incorporating both spatial and time fixed effects, the test statistics remain consistent at χ^2 = 17.21 (Wald) and χ^2 = 11.04 (LR), both significant at $p < 0.05$. Under the random-effects model, SDM continues to demonstrate superior fit over SEM, with both tests yielding χ^2 = 14.28 and χ^2 = 14.02 ($p < 0.05$).

Overall, across all model specifications, the tests consistently reject the simplification hypotheses. The spatially lagged independent variables exhibit significant explanatory power, confirming that the SDM is the most appropriate spatial regression model for this study. These findings align with the theoretical expectations of spatial interaction and regional diffusion effects, and provide a robust empirical foundation for the subsequent decomposition of spatial effects and formulation of policy recommendations.

Table 3: Spatial lag model (SLM)

Variables	Model 1 SLM with spatial fixed-effects		Model 2 SLM with time fixed-effects		Model 3 SLM with spatial and time fixed-effects		Model 4 SLM with random-effects	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
GHE	-0.008***	0.001	0.031***	0.002	-0.009***	0.001	-0.008***	0.001
PHE	427.181	758.448	-22022.220***	1431.377	1097.953	770.246	196.458	767.888
PSMI	10.693*	4.131	-15.906**	5.534	21.968***	4.234	9.501*	4.067
SAMI	-4382.768***	1028.679	-41.421	328.324	-7236.207***	1084.224	-4336.649***	945.123
PSPP	-6.085	5.018	-127.699***	12.604	-13.882*	6.334	-6.428	5.111
PSNS	72.335***	13.008	463.636***	34.607	67.556***	14.902	73.635***	13.268
Constant							31132.850*	12408.530
n		528		528		528		528
Spatial ρ	0.408***	0.039	0.146**	0.047	0.271***	0.048	0.419	0.039
within R^2	0.3769		0.0002		0.3268		0.3766	
between R^2	0.0008		0.8004		0.0166		0.0180	
overall R^2	0.0037		0.6351		0.0204		0.0263	
Log-likelihood	-5584.008		-6247.747		-5557.568		-5668.423	
Wald test	H_0: $\theta = 0$ x^2 = 12.17* p-value = 0.0484		H_0: $\theta = 0$ x^2 = 126.92*** p-value = 0.000		H_0: $\theta = 0$ x^2 = 17.21* p-value = 0.0156		H_0: $\theta = 0$ x^2 = 14.28* p-value = 0.0267	
Likelihood-ratio test	H_0: SLM nested within SDM LR x^2 = 12.00* p-value = 0.0348		H_0: SLM nested within SDM LR x^2 = 108.75*** p-value = 0.000		H_0: SLM nested within SDM LR x^2 = 11.04* p-value = 0.035		H_0: SLM nested within SDM LR x^2 = 14.02* p-value = 0.0155	

Note: * p<0.05; ** p<0.01; *** p<0.001
TWD: New Taiwan dollar (equal to USD 0.030).
SLM: Spatial lag model.
SDM: Spatial Durbin model.
Coef.:Coefficient.
Std. Err.: Standard error.
GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km²/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

Table 4: Spatial error model (SEM)

Variables	Model 5 SEM with spatial fixed-effects		Model 6 SEM with time fixed-effects		Model 7 SEM with spatial and time fixed-effects		Model 8 SEM with random-effects	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
GHE	-0.009***	0.001	0.032***	0.002	-0.008***	0.001	-0.009***	0.001
PHE	936.554	763.105	-22949.560***	1459.815	1182.140	771.872	697.725	776.061
PSMI	14.453**	4.177	-12.686*	5.230	23.324***	4.172	13.078**	4.169
SAMI	-4882.617***	1031.577	-88.700	336.807	-7420.407***	1066.094	-4714.153***	979.331
PSPP	-1.719	5.537	-133.552***	12.598	-13.890*	6.318	-2.248	5.659
PSNS	71.452***	14.026	483.254***	34.213	62.010***	14.668	72.648***	14.323
Constant							47036.650**	14854.830
n		528		528		528		528
Spatial λ	0.466***	0.047	0.223**	0.066	0.259***	0.054	0.470***	0.047
within R^2	0.3531		0.0000		0.2737		0.3526	
between R^2	0.0000		0.8079		0.0212		0.0000	
overall R^2	0.0005		0.6416		0.0244		0.0012	
Log-likelihood	-5589.697		-6244.887		-5559.115		-5677.593	
Wald test	H_0: $\theta+\rho\beta=0$ x^2 = 22.02** p-value = 0.0012		H_0: $\theta+\rho\beta=0$ x^2 = 107.91*** p-value = 0.000		H_0: $\theta+\rho\beta=0$ x^2 = 20.66*** p-value = 0.0018		H_0: $\theta+\rho\beta=0$ x^2 = 23.26*** p-value = 0.0007	
Likelihood-ratio test	H_0: SEM nested within SDM LR x^2 =23.37*** p-value = 0.0003		H_0: SEM nested within SDM LR x^2 = 103.03*** p-value = 0.000		H_0: SEM nested within SDM LR x^2 = 17.54** p-value = 0.0023		H_0: SEM nested within SDM LR x^2 = 32.36*** p-value = 0.000	

Note: * p<0.05; ** p<0.01; *** p<0.001
TWD: New Taiwan dollar (equal to USD 0.030).
SEM: Spatial error model.
SDM: Spatial Durbin model.
Coef.:Coefficient.
Std. Err.: Standard error.
GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km²/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

4.3 Results of the Hausman test

To further determine whether the Spatial Durbin Model (SDM) should adopt a fixed-effects or random-effects specification, this study applies the Hausman test proposed by Hausman (1978). The test evaluates whether the individual (county-level) or temporal random error components are correlated with the explanatory variables. If such correlation exists, the random-effects model would yield biased estimates due to endogeneity issues, and a fixed-effects model would be preferred. Table 5 presents the Hausman test statistics and inference results for three different model specifications.

First, when comparing the SDM with spatial fixed effects to its corresponding random-effects model, the test yields a χ^2 statistic of 2.95 with a p-value greater than 0.05. This result is not statistically significant, implying that we fail to reject the null hypothesis. Therefore, there is no systematic bias in the random-effects

estimator under this specification, and the random-effects model is considered appropriate in this case.

Second, under the time fixed-effects specification, the Hausman test yields a χ^2 value of 390.32, which is highly significant at the $p < 0.001$ level. This clearly rejects the null hypothesis and indicates that the random-effects model suffers from significant estimation bias. It suggests that unobserved temporal factors are likely correlated with the explanatory variables. Based on this result, the time fixed-effects model is preferred to ensure consistent and unbiased estimation.

Lastly, when comparing the SDM with both spatial and time fixed effects to its corresponding random-effects model, the Hausman test statistic is 37.50, also highly significant ($p < 0.001$). This again leads to rejection of the null hypothesis and confirms the presence of substantial estimation bias under the random-effects specification. Therefore, a two-way fixed-effects model should be adopted to control for unobserved heterogeneity across both cross-sectional and temporal dimensions, thereby enhancing the reliability of the model estimates.

In summary, except for the model with only spatial fixed effects, all other specifications indicate that the fixed-effects structure is preferable. Particularly in the cases of time and two-way fixed effects, the fixed-effects models effectively eliminate unobserved disturbances correlated with the explanatory variables, providing a robust foundation for the subsequent effect decomposition and policy implications in this study.

Table 5: Hausman Test Results

Comparison	Hausman test		Result
	x^2	p-value	
SDM with spatial fixed-effects v.s. SDM with random-effects	2.95	0.7084	$H_0: \mathrm{E}(x_{it}, \mu_i) = 0$ The null hypothesis (random-effects model) cannot be rejected; SDM with random-effects is adopted.
SDM with time fixed-effects v.s. SDM with random-effects	390.32	0.0000	$H_0: \mathrm{E}(x_{it}, \mu_i) = 0$ The null hypothesis (random-effects model) is rejected; SDM with time fixed-effects is adopted.
SDM with spatial and time fixed-effects v.s. SDM with random-effects	37.50	0.0000	$H_0: \mathrm{E}(x_{it}, \mu_i) = 0$ The null hypothesis (random-effects model) is rejected; SDM with spatial and time fixed-effects is adopted.

4.4 Spatial Durbin model analysis results

This study further employs the Spatial Durbin Model (SDM) for empirical estimation to examine the effects of government healthcare spending and medical resource allocation on county-level in-migration across Taiwan. Table 6 presents the estimation results from four different SDM specifications, including models with spatial fixed effects (Model 9), time fixed effects (Model 10), both spatial and time fixed effects (Model 11), and random effects (Model 12).

According to the results of the previously conducted Hausman tests, Model 9 and Model 12 fail to meet the statistical criteria, suggesting potential endogeneity bias or estimation inconsistency. As a result, these two models are excluded from further analysis. The focus thus shifts to the comparison and selection between Model 10 and Model 11.

To determine the optimal model, this study applies Maximum Likelihood Estimation (MLE) for parameter estimation and evaluates overall model fit using three widely accepted metrics: Log-Likelihood (LL), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Theoretically, the optimal model should exhibit the highest log-likelihood value along with the lowest AIC and BIC scores, indicating the best balance between model fit and parsimony.

The comparison results reveal that Model 11 (SDM with both spatial and time fixed effects) outperforms Model 10 across all three model fit indices. Specifically, Model 11 yields a higher log-likelihood and lower AIC and BIC values, indicating superior explanatory power and predictive performance. Consequently, this study identifies Model 11 as the preferred specification for subsequent empirical analysis, including the decomposition of spatial effects and formulation of policy recommendations.

The estimation results from Model 11 show that the spatial lag coefficient of the dependent variable is positive and statistically significant, indicating the presence of strong positive spatial autocorrelation in in-migration across counties. This implies that an increase in in-migration in neighboring counties positively influences in-migration in a given county, reflecting regional complementarity and spatial population diffusion. This spatial interaction aligns with Tobler's First Law of Geography, which posits that "everything is related to everything else, but near things are more related than distant things."

In summary, Model 11, which incorporates both spatial and time fixed effects, not only provides the best statistical fit but also effectively captures the geographic diffusion and interdependence mechanisms underlying inter-county migration behavior in Taiwan. Thus, it serves as the foundational model for the decomposition of spatial marginal effects and the development of policy simulations in this study.

Table 6: Spatial Durbin model analysis results

Variables	Model 9 SDM with spatial fixed-effects		Model 10 SDM with time fixed-effects		Model 11 SDM with spatial and time fixed-effects		Model 12 SDM with random-effects	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
GHE	-0.009***	0.001	0.032***	0.002	-0.009***	0.001	-0.008***	0.001
PHE	925.230	769.360	-19164.260***	1776.556	1310.197	778.648	804.440	779.478
PSMI	11.871**	4.216	-6.073	5.455	22.243***	4.889	11.320**	4.150
SAMI	-4456.690***	1026.810	-1391.783***	332.778	-7076.061***	1291.650	-4521.102***	944.016
PSPP	-4.041	5.656	-134.781***	11.525	-12.668*	6.344	-4.553	5.755
PSNS	57.207***	14.666	468.733***	33.136	63.541***	15.066	56.917***	14.781
W×GHE	0.006**	0.002	-0.003	0.005	0.001	0.002	0.006**	0.002
W×PHE	-1682.740	2269.938	36111.970***	7358.354	3430.470	2835.953	-1454.294	2310.463
W×PSMI	17.460	15.526	-31.362**	9.195	26.250	16.469	17.083	14.043
W×SAMI	-796.233	2926.858	-717.375	926.134	-4572.976	2994.044	690.342	2452.822
W×PSPP	1.378	9.526	91.304**	28.432	-9.496	12.812	1.491	9.552
W×PSNS	0.990	20.813	-285.114***	69.021	15.960	27.865	-2.052	21.200
Constant							4763.757	16098.550
n		528		528		528		528
Spatial ρ	0.421***	0.046	0.246***	0.062	0.250***	0.056	0.429***	0.045
within R^2	0.3952		0.0385		0.3198		0.3948	
between R^2	0.0459		0.8654		0.0389		0.0824	
overall R^2	0.0564		0.6452		0.0431		0.0941	
Log-likelihood	-5578.010		-6193.373		-5553.797		-5661.412	
AIC	11178.02		12406.75		11129.59		11346.82	
BIC	11224.98		12449.44		11176.55		11398.05	

Note: * p<0.05; ** p<0.01; *** p<0.001
TWD: New Taiwan dollar (equal to USD 0.030).
SDM: Spatial Durbin model.
Coef.:Coefficient
Std. Err.: Standard error.
GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km²/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

4.5 Decomposition results of the SDM with spatial and time fixed-effects

According to LeSage and Pace (2009), the Spatial Durbin Model (SDM), which simultaneously incorporates spatial lags of both the dependent and independent variables, offers a more comprehensive framework for modeling interregional interactions. However, this structure also introduces the phenomenon of spatial feedback effects, wherein the indirect effect of an explanatory variable on neighboring regions can, through spatial linkages, loop back to influence the

dependent variable in the focal region. This mechanism implies that relying solely on raw coefficient estimates may result in biased interpretations, as they capture only first-order effects and fail to reflect the complete diffusion and feedback processes inherent in spatial systems.

To address this, LeSage and Pace (2009) emphasize the importance of impact decomposition in spatial econometric modeling, whereby the marginal effects of each explanatory variable are disaggregated into three components: direct effects, indirect effects (i.e., spatial spillovers), and total effects (the sum of direct and indirect effects).

Following the matrix computational approach proposed by Elhorst (2010), this study performs marginal effect decomposition on the previously identified optimal model—SDM with spatial and time fixed-effects. The estimated direct, indirect, and total effects of each explanatory variable are presented in Table 7, alongside robust standard errors to evaluate the statistical significance and substantive implications of these effects.

The results show that government healthcare expenditure (GHE) exerts a significant negative direct effect on in-migration, with an estimate of −0.009 ($p < 0.001$). Its indirect effect is statistically insignificant, while the total effect is −0.010 and remains significant at the 1% level. This finding indicates a clear discouraging effect of local government healthcare spending on in-migration at the county level, without evidence of regional spillover.

In contrast, the proportion of healthcare spending in total government expenditure (PHE) shows a positive estimated effect, but neither the direct, indirect, nor total effects are statistically significant. This suggests that as a ratio-based fiscal indicator, PHE may have limited short-term influence on migration decisions, or its impact might manifest only in interaction with other contextual variables.

Regarding medical resource allocation, the variable average number of persons served per medical institution (PSMI) exhibits significant positive direct and indirect effects, with estimates of 24.476 ($p < 0.001$) and 35.743 ($p < 0.05$), respectively. The total effect is 60.219 and significant at the 1% level. This indicates that higher service density (i.e., more people served per institution) is associated with stronger population inflows, reflecting both local and regional-level attraction mechanisms.

On the other hand, average service area per medical institution (SAMI) has a strong negative impact, with a direct effect of −7537.417 ($p < 0.001$) and an indirect effect of −6954.378 ($p < 0.05$), yielding a total effect of −14491.790. These findings suggest that overly dispersed spatial allocation of medical facilities significantly diminishes regional attractiveness and exerts negative externalities on adjacent areas.

Turning to healthcare manpower variables, average number of people served per practicing physician (PSPP) shows a negative direct effect of −13.636 ($p < 0.05$), while the indirect and total effects are not significant. This implies that physician density primarily influences in-migration through local supply conditions and has limited regional spillover. In contrast, average number of people served per nursing

staff (PSNS) yields a positive direct effect of 66.162 ($p < 0.001$) and a total effect of 102.461 ($p < 0.01$), suggesting that nursing resources exert a stronger pull on in-migration, possibly due to their critical roles in primary healthcare and long-term care services.

In sum, the SDM effect decomposition reveals that variables such as PSMI, SAMI, and PSNS possess both significant direct and indirect effects, indicating that their influence extends beyond the local level and generates meaningful spatial externalities through geographic proximity. These findings underscore the analytical limitations of conventional regression coefficients in spatial settings and highlight the necessity of decomposition methods to accurately understand the spatial mechanisms embedded in population migration behavior.

Table 7: Direct, indirect, and total effects of SDM with spatial and time fixed-effects

Variables	Direct Effect		Indirect Effect		Total Effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
GHE	-0.009***	0.001	-0.001	0.003	-0.010**	0.003
PHE	1481.309	790.579	4010.573	2843.909	5491.881	3153.059
PSMI	24.476***	4.762	35.743*	17.621	60.219**	19.180
SAMI	-7537.417***	1238.298	-6954.378*	3273.629	-14491.790*	3826.356
PSPP	-13.636*	6.187	-14.998	13.684	-28.635	16.492
PSNS	66.162***	15.380	36.298	31.216	102.461**	38.358

Note: * p<0.05; ** p<0.01; *** p<0.001
TWD: New Taiwan dollar (equal to USD 0.030).
Coef.:Coefficient.
Std. Err.: Standard error.
GHE: Government Healthcare Expenditure (NT$1,000), PHE: Proportion of Healthcare Expenditure to Total Government Expenditure (%), PSMI: Average Population Served per Medical Institution (persons/institution), SAMI: Average Service Area per Medical Institution (km²/institution), PSPP: Average Population Served per Practicing Physician (persons/physician), PSNS: Average Population Served per Nursing Staff (persons/nurse).

5. Conclusion and Suggestions

5.1 Conclusion

This study investigates how national health insurance (NHI) expenditures and the allocation of medical resources influence inter-county in-migration patterns in Taiwan, with particular emphasis on the spatial spillover effects and proximity-based interaction mechanisms embedded in such processes. By constructing a panel dataset at the county level spanning from 2000 to 2023 and employing the Spatial Durbin Model (SDM) from the spatial econometrics framework, this research successfully captures the spatial relationships between migration behavior and healthcare investment, thereby addressing the estimation biases that may arise when traditional regression models neglect spatial dependence.

The empirical results indicate that the SDM model with both spatial and temporal fixed effects provides the most appropriate estimation framework. The impact decomposition analysis reveals that several variables exert significant influence at

both the local and neighboring levels, underscoring the spatial interdependence and regional complementarity inherent in migration decisions. Among the key findings, the density and accessibility of medical institutions emerge as critical factors in attracting in-migration: the average number of people served per medical institution (PSMI) and the average number of people served per nurse (PSNS) have significant positive effects on in-migration, with observable spillover effects extending across adjacent counties. In contrast, the average service area per medical institution (SAMI) and the average number of people served per practicing physician (PSPP) show negative associations, suggesting that diluted or uneven distribution of medical resources diminishes a region's attractiveness to potential migrants.

Additionally, while government healthcare expenditure (GHE) exhibits a significant negative effect on in-migration at the local level, it does not produce significant spatial spillover effects. This may imply that central government subsidies do not effectively translate into immediately accessible local medical services, thereby becoming a potential disincentive for population inflow.

This study also empirically validates the Tobler's First Law of Geography in the context of migration decision-making. It demonstrates that adjacent counties, due to their geographical proximity, exert interactive influences on each other's medical and social resource configurations, which in turn shape migration patterns through spatial linkages. Thus, migration is not solely a response to the characteristics of a given destination but also a comparative judgment shaped by the relative conditions of neighboring regions. This finding carries strong policy implications for regional integration, equitable distribution of healthcare resources, and the formulation of urban-rural population balancing strategies.

In summary, this research confirms that both healthcare expenditure and medical resource allocation are key determinants of in-migration at the county level, with significant spatial heterogeneity and spillover effects. These insights highlight the importance of adopting an integrated spatial perspective in future regional demographic policy planning. Policies formulated in isolation, without regard for interregional interactions, may overlook critical dynamics and inadvertently exacerbate regional inequalities. Therefore, fostering balanced development and rational population mobility requires comprehensive spatial coordination and intergovernmental collaboration.

5.2 Policy Suggestions

This study reveals that healthcare resource allocation and NHI (National Health Insurance) expenditures at the county level exert significant influence on in-migration patterns, with clear evidence of spatial spillover effects and inter-regional interactions. These findings underscore that in the context of population mobility and regional development in Taiwan, healthcare accessibility and the quality of public services have emerged as critical determinants in individual migration decisions. In light of these insights, future regional development and population policies should transcend conventional administrative boundaries, shifting toward a

"functional regions" perspective that emphasizes inter-county collaboration and shared healthcare infrastructure.

First, to address the issue of overly concentrated or unevenly distributed healthcare resources, the central government should recalibrate its policies on the allocation of medical facilities and human resources. In particular, for remote or aging counties experiencing population decline, financial incentives should be employed to encourage the establishment of primary healthcare stations and the recruitment of nursing personnel, thereby improving overall service accessibility. Based on this study's findings, variables such as people served per nurse (PSNS) and people served per medical facility (PSMI) are positively associated with in-migration, suggesting that enhancing access to basic healthcare services can help stabilize local populations and attract new residents.

Second, the negative relationship observed between government healthcare expenditure (GHE) and in-migration implies that centralized transfer payments may not be effectively translating into tangible improvements in healthcare accessibility or quality at the local level. Hence, the mechanisms by which NHI and public health budgets are implemented regionally warrant reconsideration. It is recommended that national health authorities incorporate indicators such as "population attraction potential" and "regional service demand" into budget allocation criteria. This would strengthen the outcome-oriented principle of fiscal resource distribution and ensure that public spending contributes meaningfully to shaping local demographic structures and enhancing population mobility.

Third, in light of this study's demonstration that healthcare conditions in neighboring regions affect local in-migration through spatial spillovers, policy planning should avoid "zero-sum competition" among counties. Instead, efforts should be made to promote the outward diffusion of urban medical services, develop regional healthcare networks, and expand telehealth systems. These approaches can reduce disparities in healthcare accessibility across regions and support the formation of balanced urban-rural functional zones or regional alliances, thereby enhancing both geographic mobility efficiency and regional resilience.

Finally, the spatial interaction effects revealed by the econometric model serve as a critical reminder to policymakers: the impacts of healthcare policies often extend beyond a single administrative unit, potentially triggering chain reactions that affect surrounding counties. Thus, any major adjustments in medical resource allocation, facility consolidation, or institutional reforms should be preceded by comprehensive regional impact assessments. This foresight can help mitigate risks such as population displacement or rural-urban healthcare fragmentation, ultimately ensuring that population and resource allocation policies align with the long-term goal of balanced and sustainable regional development.

References

[1] Balia, S., Brau, R., & Marrocu, E. (2018). Interregional patient mobility in a decentralized healthcare system. Regional Studies, 52(3), 388–402.

[2] Baltagi, B. H., Moscone, F., & Santos, R. (2018). Spatial Health Econometrics, Contributions to Economic Analysis, in: Health Econometrics, 127, 305-326, Emerald Group Publishing Limited.

[3] Directorate General of Budget, Accounting and Statistics (DGBAS) of the Executive Yuan (2024) County/City Major Statistical Indicators Query System Found in the Statistical Information Network. Dataset, DGBAS. Available at: https://winstacity.dgbas.gov.tw/DgbasWeb/ZWeb/StateFile_ZWeb.aspx (accessed 25 December 2024).

[4] Dong, X., & Wang, Y. (2024). The geography of healthcare: Mapping patient flow and medical resource allocation in China. Economics & Human Biology, 55, 101431.

[5] Elhorst, JP (2010). Applied spatial econometrics: Raising the bar. Spatial Economic Analysis, 5(1), 9–28.

[6] Finkelstein, A., Gentzkow, M., & Williams, H. (2016). Sources of geographic variation in health care: Evidence from patient migration. The Quarterly Journal of Economics, 131(4), 1681–1726.

[7] Guo, Q., & Luo, K. (2019). Concentration of healthcare resources in China: The spatial–temporal evolution and its spatial drivers. International Journal of Environmental Research and Public Health, 16(23), 4606.

[8] Hausman, J.A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251–1271.

[9] LeSage, J., and Pace, K.R. (2009). Introduction to Spatial Econometrics. New York: CRC Press, Taylor & Francis Group.

[10] Moscone, F., & Knapp, M. (2005). Exploring the spatial pattern of mental health expenditure. Journal of Mental Health Policy and Economics, 8(4), 205–217.

[11] Pan, J., & Shallcross, D. (2016). Geographic distribution of hospital beds throughout China: a county-level econometric analysis. International Journal for Equity in Health, 15, 179.

[12] Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. Economic Geography, 46, 234–240.

[13] Wan, S., Chen, Y., Xiao, Y., Zhao, Q., Li M., & Wu, S. (2021). Spatial analysis and evaluation of medical resource allocation in China based on geographic big data. BMC Health Services Research, 21, 1084.

[14] Wang, S., & Wan, M. (2024). Population mobility: Spatial spillover effect of government health expenditure in China. Global Health Action, 17(1), 2319952.

[15] Zhang, R., Li, J., Du, X., Ma, T., Zhang, L., Zhang, Q., & Xia, F. (2019). What has driven the spatial spillover of China's out-of-pocket payments? BMC Health Services Research, 19, 610.